



Research on Cross-cultural Education Communication Platform based on Artificial Intelligent

Mingyu Cui, Nor Azni Binti Abdul Aziz*, and Aminuddin Bin Hassan

Universiti Putra Malaysia, Faculty of Educational Studies, Malaysia

*nor.azni@upm.edu.my

Abstract. In today's increasingly globalised world, international exchanges and cooperation are becoming more frequent, and the resulting intercultural conflicts are on the rise. In order to reduce misunderstandings caused by cultural differences, research on intercultural communication is in full swing. Cross-cultural knowledge, which refers to the knowledge of universal laws in different countries or nations, as an important factor in cross-cultural communication has also gradually received attention. This work proposed an AI-based cross-cultural education communication platform, which is designed with the objective of overcoming the communication barriers that arise in different cultural contexts. The principal methodologies encompass the utilisation of natural language processing technology for the translation of multilingual texts, the integration of sentiment analysis models to discern and comprehend the implicit emotional nuances across diverse cultural contexts, and the interconnection and recommendation of cultural knowledge through the application of knowledge graph technology. The implementation of the platform employs deep learning models to train language translation and sentiment analysis, and optimises and tests them with large-scale cross-cultural datasets. The results of the experimental phase demonstrate that the platform has significant advantages in terms of improving the accuracy and efficiency of cross-cultural communication.

Keywords: Cross-cultural Education Platform, Natural Language Processing, Sentiment Analysis, Knowledge Graph.

1 INTRODUCTION

The interpretation of the same phenomena may vary considerably between countries, due to a number of factors, including the country's unique historical background, living habits, religious beliefs and other cultural influences. These disparate perspectives do not constitute objections to the objective form of existence; rather, they give rise to different cultural and metaphorical meanings once these entities are imbued with national values and a national spirit. As a means of comprehending the objective world, metaphor facilitates the clarification of unfamiliar concepts by juxtaposing the known with the unknown^[1].

When individuals encounter two entities that exhibit analogous characteristics in their lived experiences, they frequently transfer the representation of one entity to another, thereby establishing a metaphorical relationship. The study of cross-cultural metaphors constitutes an essential component of cross-cultural common sense research. Its emergence and evolution are profoundly shaped by the distinctive historical, religious, and socio-cultural traditions of each nation^[2]. A deeper understanding of cross-cultural metaphors facilitates more effective communication and interaction in diverse cultural contexts.

In the context of the accelerated pace of globalisation and the increasing integration of information technology, international educational exchanges have become a prominent feature of the contemporary educational landscape. The collaboration and exchange of talent in the field of education between countries has emerged as a pivotal driving force in the advancement of the global knowledge economy^[3]. Nevertheless, it would be erroneous to assume that cross-cultural educational exchanges are always straightforward. Cultural dissimilarities, linguistic obstacles and the coexistence of disparate educational frameworks frequently result in miscommunication and recurrent misinterpretations in cross-cultural interactions.

To illustrate, nonverbal or context-dependent expressions in some cultures may result in misinterpretation in another^[4]. Furthermore, the existence of language barriers often makes it challenging to achieve the desired effect in the transmission of educational content and the understanding of educational concepts in cross-cultural communication. Such miscommunication and misunderstanding not only impede the smooth progression of exchanges but may also diminish the efficacy and efficiency of educational cooperation, thereby constraining the scope for international collaboration and educational innovation^[5].

Artificial intelligence technology provides new opportunities to solve many problems in cross-cultural communication. Taking natural language processing as an example, this technology can achieve efficient processing and instant translation of multilingual texts, so that users with different language backgrounds can communicate and learn without barriers^[6]. In addition, sentiment analysis technology can deeply identify and understand the expression of emotions in different cultural contexts and their implicit cultural connotations, so as to avoid communication barriers caused by emotional misunderstandings. For example, different cultures may express the same emotion in very different ways, and sentiment analysis technology can accurately capture these differences and adapt by learning from large amounts of cross-cultural data.

2 RELATED WORK

Xia et al.^[7] proposed a cross-cultural intelligent language learning system called CILS, which aims to enhance cross-cultural communication skills in language education through artificial intelligence technology. The CILS system integrates advanced adaptive learning technology that dynamically adapts content and teaching methods to the learner's linguistic and cultural background, resulting in significant improvements in language proficiency and cultural understanding.

Additionally, Long et al.^[8] discussed the application of AI-based English teaching models in cultivating cross-cultural communication competence of college students. The study shows that AI technology can significantly improve students' performance in cross-cultural communication, especially with the support of 5G network technology, AI can provide more contextual and personalized language teaching, and enhance students' cross-cultural understanding and adaptability

Shadiev et al.^[9] detailed key trends and key findings in the field by analyzing 31 studies related to technology-enabled cross-cultural learning published in 25 journals over the past 20 years. The article points out the growing popularity of remote collaboration tools, virtual reality technologies, and artificial intelligence platforms in cross-cultural learning, and explores the advantages and limitations of these technologies. Finally, this paper proposes that future research should pay more attention to the deep integration of emerging technologies and cross-cultural learning, which provides guidance for designing more intelligent and interactive learning environments

3 METHODOLOGIES

3.1 Neural Machine and Sentiment Analysis

Above all, the platform uses a deep learning-based Neural Machine Translation (NMT) model for multilingual text translation. NMT models typically employ an encoder-decoder structure, where the encoder converts the input source language sentence into a context vector, and the decoder generates sentences in the target language based on this context vector. For a source language sentence $X = (x_1, x_2, \dots, x_n)$, the model's goal is to find the target language sentence $Y = (y_1, y_2, \dots, y_m)$ so that the probability of that sentence is maximized, which is expressed as Equation 1.

$$P(Y|X) = \prod_{t=1}^m P(y_t | y < t, X; \theta) \quad (1)$$

Where θ is the parameter of the model and $y < t$ is the target language word generated before time step t . Encoders typically employ a bidirectional LSTM network that encodes the input sequence as a context vector h_t . The decoder generates the output of the target language based on the context vector, which is described as Equation 2.

$$s_t = LSTM(y_{t-1}, s_{t-1}, c_t) \quad (2)$$

Where c_t is a context vector extracted from the encoder state via an attention mechanism to capture the correspondence between the source and target languages. In order to identify and understand the implicit emotional expressions in different cultures, sentiment analysis models based on recurrent neural network were used. At its core, sentiment analysis models extract features from text and determine sentiment tendencies. For an input text sequence $T = (t_1, t_2, \dots, t_n)$, the sentiment analysis model calculates the conditional probability of the sentiment label y is expressed as Equation 3.

$$P(y|T) = \text{softmax}(W \cdot f(T) + b) \quad (3)$$

Where W is the convolutional kernel, $x_{i:i+k-1}$ is part of the input text sequence, and k is the size of the convolutional kernel. The pooling layer is used to reduce the dimensionality of a feature, and the maximum pooling operation commonly used is $\max(h_1, h_2, \dots, h_n)$.

3.2 Knowledge Graph

Knowledge graphs are typically represented by triples (h, r, t) , where h is the head entity, r is the relation, and t is the tail entity. The embedding model of the knowledge graph maps these triples into a low-dimensional vector space and is trained by optimizing the objective function, which is expressed as Equation 4.

$$L = \sum_{(h,r,t) \in T} \log \sigma(\gamma - d(h + r, t)) + \sum_{(h',r',t') \in T'} \log \sigma(d(h' + r, t') - \gamma) \quad (4)$$

Where γ is the boundary parameter, d is the distance function, T is the positive sample set, and T' is the negative sample set.

The application of knowledge graph technology is to realize the association and intelligent recommendation of cultural background information, so as to help users better understand and adapt to different cultural backgrounds. Queries allow users to get all the information related to a particular entity from the knowledge graph or explore the complex relationships between entities. For example, users can query "the participants of a particular cultural event and their subsequent impacts" and get a complete picture of the relevant entities and their associated information.

The graph neural network updates the embedding representation of each node through a messaging mechanism and expresses as Equation 5.

$$h_v^{(k)} = \sigma(W^{(k)} \cdot \text{Aggregate}(\{h_v^{(k-1)}, \forall u \in N(v)\}) + b^{(k)}) \quad (5)$$

Where $h_v^{(k)}$ represents the embedding representation of node v at layer k , $N(v)$ represents the set of neighbor nodes of node v , $W^{(k)}$ and $b^{(k)}$ are the weight matrix and bias of layer k , and $\sigma(\cdot)$ is the activation function. Through multi-layer stacking, graph neural networks can gradually capture deeper relationship information, thereby enhancing the reasoning ability of knowledge graphs.

Knowledge graph not only provides rich background knowledge in the cross-cultural education exchange platform, but also enhances the user experience through intelligent recommendation and reasoning, making learning and communication in different cultural backgrounds more effective and meaningful.

4 EXPERIMENTS

Above all, We identified the goals and features through a requirements analysis, and then made wireframes and prototypes to plan the page layout and user interactions. Next, we worked on the visual design, choosing fonts, color schemes, and designing a

responsive layout. In the front-end development phase, we implemented the design using HTML, CSS, and JavaScript to ensure compatibility and a good user experience. Once completed, we conducted thorough testing and optimization, and finally deployed the website live and continued to maintain it.

This process ensures the perfect combination of aesthetics and functionality for the website, providing users with a premium experience. Following Figure 1 shows the general website of proposed platform for cross-cultural educational exchanges.



Fig. 1. Illustration of platform for cross-cultural educational communication.

We introduce an AI-based cross-cultural education communication platform that aims to overcome communication barriers in different cultural contexts. Key features include the use of natural language processing technology to translate multilingual texts, the integration of sentiment analysis models to understand and grasp the nuances of emotion in different cultures, and the connection and recommendation of cultural knowledge through knowledge graph technology. The platform is trained on language translation and sentiment analysis through deep learning models, and optimized and tested using large-scale cross-cultural datasets to ensure accurate and effective cross-cultural communication solutions. Following Figure 2 illustrates the module of artificial components.

Services

AI-Based Communication Platform

This work proposes an AI-based cross-cultural education communication platform designed to overcome communication barriers in diverse cultural contexts. The methodologies include utilizing natural language processing technology for translating multilingual texts, integrating sentiment analysis models to understand emotional nuances, and using knowledge graph technology to interconnect and recommend cultural knowledge. The platform employs deep learning models for training language translation and sentiment analysis, optimizing them with large-scale cross-cultural datasets.

Fig. 2. Illustration of artificial intelligent module of platform.

5 CONCLUSION

In conclusion, the Cross-Cultural Education Communication Platform harnesses the power of advanced AI technologies, including natural language processing for multi-language translation, sentiment analysis for emotional understanding, and knowledge graph technology for cultural insights and recommendations. The platform's design, which integrates these sophisticated tools, aims to bridge cultural gaps and enhance global communication by providing users with tailored, interactive learning experiences. The website's homepage effectively showcases these features, ensuring accessibility and user engagement while fostering a deeper understanding and appreciation of diverse cultures. As a result, this platform stands as a crucial tool for promoting cross-cultural competence in an increasingly interconnected world.

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